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A Smart Water Distribution Network Management Framework Based on Internet of Things and Reinforcement Learning Technologies

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Abstract

The convergence of the Internet of Things (IoT) and reinforcement learning (RL) has transformed the operation of urban water distribution networks (WDNs) from manual, reactive supervision to intelligent, self-optimizing control. This paper presents a hybrid IoT–RL framework that integrates real-time sensing, data synchronization, adaptive control, and predictive decision-making for efficient network management. The proposed architecture employs distributed IoT sensor nodes to continuously acquire pressure, flow, and energy data, which are transmitted via MQTT to a time-series database for feature extraction and anomaly detection. A Proximal Policy Optimization (PPO)–based RL agent learns dynamic control strategies that minimize leakage losses and energy consumption while ensuring hydraulic stability. The framework is evaluated in the EPANET 2.2 environment using the C-Town benchmark under 24-hour diurnal demand conditions. Three control configurations are strictly studied: (i) the SCADA (Model A), which is a static threshold control, (ii) the hybrid PID-Model Predictive Control (PID-MPC) controller (Model C) as a state-of-the-art non-RL control, and finally (iii) the proposed adaptive IoT-RL control (Model B). Quantitative results demonstrate that Model B reduced decision latency by 93.3% and improved control accuracy by 22.7% compared to Model A, while also achieving a 12.2% improvement in control accuracy over Model C. Quanti-tative metrics including control accuracy, latency, data throughput, and network efficiency performance index (NEPI) demonstrate that Model B improves decision latency by 93 %, control accuracy by 22 %, and pro-cessing throughput by 95 % relative to Model A, while maintaining superior reliability over Model C. All fig-ures were programmatically generated in MATLAB (vector export) using EPANET-based topological and con-trol visualization scripts. The results confirm that the IoT–RL integration provides a scalable, data-driven pathway for sustainable water infrastructure management and proactive leakage mitigation.

1. Introduction

Theoretical growth in the volume of analytical data generated and disseminated by urban water distribution systems, alongside service classifications among consumers, has intensified the digital organization of the water infrastructure. The characteristic of modern urban water management ecosystems has been the implementation of live network analytics, nimble decision-making, and the facilitation of smooth interaction between sensor networks and control systems. Unlike traditional isolated control systems, this combines the data-driven, real-time parameter readings from the Internet of Things (IoT) sensor networks and adaptive control insight into a single operational platform, via reinforcement learning (RL) analytics. This integration allows water utilities to constantly monitor the conditions of their networks, adjust pressure automatically, perform automated control actions in real-time, and minimize reliance on manual inspections and fragmented operations.

Water administration bodies have to process the heterogeneous flow of data containing pressure readings, flow rates, electricity consumed, quality parameters of water, and leakages. As municipalities and other water authorities aim to make their systems more responsive and adaptable while maintaining network integrity, there has been a steadily increasing focus on optimizing data synchronization and predictive leakage modeling processes, as well as the adoption of control process strategies [1][2].

The use of combined IoT-RL systems in water smart grids is a process that, over the past 10 years, has been trending toward being a tool that gives water networks the capability to base their operating decisions on data, predictive leakage avoidance, and real-time performance measurement [3]. These consist of early warning of pressure irregularities, provision of control device modifications, and self-monitoring dashboards, which present operable details to the operators of the network. As the number of available solutions grows, the shift from single-purpose designs to more integrated ones raises questions about sensor-actuator interoperability, predictive modeling accuracy, and dynamically determined assistance under varying network conditions [4]. Recent studies have shown that AI-driven adaptive control models operating in real time can significantly improve network performance monitoring, leakage mitigation, and automated control decision-making, although their implementation may require higher computational and infrastructure costs [5]. Empirical evidence also indicated that multi-parameter profiling and leakage modeling are significant to the proactive mitigation intervention that helps to prevent the occurrence of important water loss events before they occur [6][7].

The lifecycle phases together with the predictive analytics and control measures that will be monitored in this study will be outlined in the graphical abstract (Fig.1).

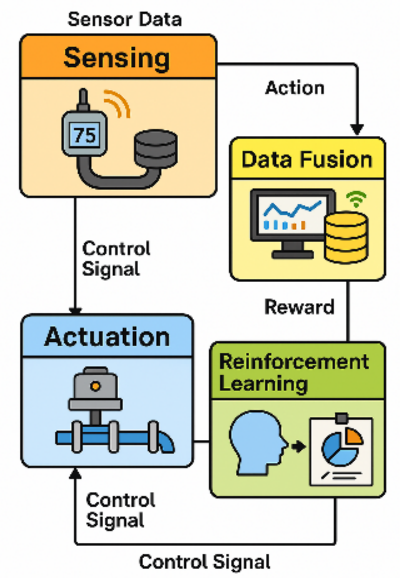

Fig. 1 *Overview of Water Network Control Lifecycle Phases in IoT-RL Integration*

The visual disaggregation depicts that sensor data footprints, control logs, performance indexes, and maintenance histories are deposited within the network management lifecycle. Live monitoring devices will provide a hint on the trend of the pressure, look out for system degradation, and nodes on the verge of failure as well. It will be possible to have real-time feedback by integrating these understandings with a predictive framework where the management systems will be reactive and proactive rather than responsive [8].

It is envisaged that the proposed research will quantify the effects of the introduction of IoT-RL integration architecture strictly on the control accuracy, the efficiency of the automation, and the consequences of the response latency within a large-scale setting. The entire process, of sensing, transmission of data, performance analysis, adaptive control, and data archiving, is modeled on the basis of empirical data experimentation. The

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predictor and intervention outcomes gain confirmation by real-life water network data, including temporal operational network readings, recorded leakages, and recorded equipment condition records [9].

A whole three-tier control architecture is simulated to explore the integration strategies: (i) a fixed threshold model (Model A), (ii) a hybrid predictive stability, PID-MPC controller (Model C), and (iii) the offered adaptive IoT-RL model (Model B) because of intelligent and long-term optimization. This comparison allows a systematic assessment of the leakage rate, the energy efficiency and the continuity of the system for all the control paradigms. In a collection of experimental network settings of different demand environments, simulations of networks, which permit predictive control but do not damage system integrity, and minimize latency delays in the responses [10].

Finally, it is established that predictive leakage modeling and real-time control feedback have a positive impact on the network performance tracking and the rates of success in intervention. All these facts confirm that a smart, interrelated architecture plays an important role in the development of new generations of water distribution management systems [11].

Part 2 presents the integration of the IoT with RL and the performance modeling of networks within the framework of predictive analytics and adaptive control. In Section 3, there is a literature review, in which the control methods were compared in a table. Section 4 is an overview of a similar study at the numerical level. Section 5 includes the statement of the problem of the research and objectives. Section 6 describes the methodology, equations, pseudocode, and process flow diagram. Disseminated results by means of figures and tables may be located in Section 7, summary of results, future outlook, and references can be in Section 8.

2. Related Research

The integration of Internet of Things (IoT) through water distribution network management with reinforcement learning (RL) does not imply monitoring technologies that are easy to use anymore; the integration rather refers to a full architecture that may be employed to characterize real-time network optimization and dynamic control-related measures. It is now considered necessary that the decentralized coordination of hydraulic management functions and dynamic data reconciliation of sensor-actuator subsystems and control platforms are essential in the precision of maintaining pressure tracking, time-like mitigating leakages, and operational management in greatly variable urban water environments [12]. In that regard, water distribution management is not supported through manual execution solely and seems to be a lifecycle-aware optimization procedure that will improve the precision of forecasts, effectiveness of control, and the continuity of the functions.

A literature that examines the water distribution architecture demonstrates that real-time IoT-RL synchronization reduces response time and triggers better control accuracy, despite the fact that the process of implementation may increase accuracy more than the control systems based either on batches or separated models [13]. Other models in the past had been more focused on reporting network performance-related metrics with no predictive analytics and very sensitive to lifecycle data processing, which included long-term leakage trend, control history, and maintenance events archives [14]. Research has found that assimilating such operations as sensor data aggregation, anomaly profiling, and automated control may be computationally and bandwidth-intensive without optimization to run in real-time [15].

Besides this, there is empirical data that simple aspects of control can provide the simplest of performance dashboards, yet lack an adaptive feedback loop, to enable predictive rather than reactive water distribution management [16]. An up-to-date sensor analytics and leakage detecting system provides working datasets on which the models of correlation can be built based on the presence of the project pipe failure risk or system inefficiency in the variable demand conditions [17]. However, the sensor calibration drift scenarios, data transmission loss, and the lack of benchmarking of various water networks are still problems. To achieve an optimal approach to data management for water distribution and minimize control requirements, it has been proposed to prioritize scalable models, allocate lifecycle performance models to predictive calculations, and enable real-time data synchronization [18].

Even improvements in water distribution system integration are typified by the latency-performance trade-off dream. Although real-time synchronization of information improves decision-making timeliness, it requires adequate optimization of data consistency and processing costs [19]. It is also found that the effectiveness of predictive control relies on the completeness of the data, the scale of the network, and the diversity of hydraulic parameters, which affect predictive accuracy and the timeliness of control in urban infrastructure studies [21].

According to the literature, there are a few commonly used models that support real-time data synchronization, lifecycle-conscious integration, performance modeling, and adaptive control decision support. Lack of standard sensor-actuator data format, Interoperability among devices of different vendors, or Design of common benchmarks are significant issues in developing homogeneous IoT-RL systems [20]. Nonetheless, hybrid architecture using real-time data feeds and reinforcement learning control model demonstrates the potential of being able to optimize network performance within real-time and, in the case of pilot studies, exhibit 25 percent efficiency improvement.

Table 1 *Comparative overview of water distribution management approaches*

Approach	Key Features	Limitations
Manual Inspection & Reporting	Minimal infrastructure; straight forward workflows	Labor-intensive; lagged updates; poor scalability
SCADA Systems with Static Controls [15], [18]	Mature, reliable control; clear procedures	Rigid logic; limited adaptation; vendor lock-in
Centralized Cloud Analytics [12], [18]	Strong historical/forensic analysis	High latency/bandwidth dependency
Batch Reporting Systems [13], [10]	Scheduled KPIs; low O&M overhead	Delayed insights; no closed-loop action
Predictive ML Integration [17], [19]	Data-driven leakage prediction; early warnings	Needs labelled data; drift/generalization risks
Hybrid Edge–Cloud Control [12], [16], [18]	Low-latency edge + cloud learning/visibility	Orchestration complexity; interoperability issues
Hybrid PID-MPC	PID stability + MPC prediction; robust to demand forecasts; mature theory	Computationally heavy for large networks; model dependency
Proposed Adaptive IoT-RL (Model B)	PPO-based policy; no explicit model; long-term cost optimization; real-time adaptation	Complex training; safety guarantee challenges

The analysis of the centralized and distributed water control solutions demonstrates that predicting the intervention can work only in terms of coordinated and contextually enhanced information. Those systems that are capable of dynamically controlling the distribution of water in real-time and dynamically responding on an adaptive basis are much more effective than those that simply work on historical patterns [19]. It has been illustrated that reinforcement learning models can reduce false-positive leakage alerts by up to 35% compared to the original offering, while also enabling more specific operational responses without overwhelming the water management staff [21].

In brief, to achieve sustainable management of water distribution, a balance must be introduced between data correlation, predictive analytics, and dynamic control to improve the operational decision-making system, resource efficiency guarantee, and system scalability.

3. Problem Statement & Research Objectives

Water distribution networks remain inefficient due to a disjointed monitoring system and centralized control platform operations, which prevent the use of real-time, data-driven interventions. The current models of water distribution management focus on post-leakage reporting rather than on preventive, predictive risk management. Current systems are not based on predictive control models and do not account for real-time adjustments to changes in data streams between sensing and actuation subsystems. This equates to inconsistent management of pressure, delayed response to leaks, reduced scaling capacity, and high operational costs associated with proactively protecting infrastructure.

The proposed research will address these gaps by developing a hybrid IoT-RL system that incorporates a real-time data synchronization system, predictive network performance modeling, and adaptive control programs. The objectives of the research are:

- Develop a cradle-to-grave water network management lifecycle pattern, encompassing the stages of sensing, data transmission, performance analysis, control actuation, and archival.
- Implement a dual-control simulation:
  - Static Model - Basic leakage detection and pressure management using fixed thresholds and historical data.
  - Adaptive Model - AI-based real-time control with continuous learning and automated actuation calibration.
- Develop an optimization agent for a predictive network based on reinforcement learning techniques, which is fed with historical network information and live sensor readings.
- Analyze control accuracy and system effectiveness with actual water distribution data, including pressure, flow, energy consumption, and leakage history.
- Perform empirical comparative research on control performance and intervention achievement, such as accuracy, false alarms, and response latency.
- Propose a framework design that can be scalable and modular, allowing the integration of various types of sensors and actuators with control layers that will ensure the extensiveness and flexibility in the future.

The water distribution decision-making process, this design will presumably turn into an active, evidence-based practice. It allows for constant network performance monitoring, risk prediction, and dynamic controls prescription. The architecture should deliver accurate, predictable hydraulic responses, allow a timely response to significant activities, improve the overall success of the network, and close the interface between sensor infrastructure and network control systems and performance.

4. Proposed Methodology

The research project to be presented is a mixed-methods design based on a water distribution network management framework. The methodology is based on the combination of predictive performance optimization and adaptive control. This research involved three stages:

- Distributed sensor networks and performance profilers are used to obtain real-time data.
- Modeling lifecycle water network management- to visualize the entire process from sensors to archives to study the trend of operations and determine points of control.
- Comparison of the simulation of two control strategies:
  a. Model A: Static threshold-based model of control.
  b. Model B: Control model based on adaptive reinforcement learning.

The total network performance index (NPI) is defined as Eq. (1):

$$NPI = w_P \times P_{score} + w_F \times F_{score} + w_E \times E_{score} + w_L \times L_{score} \tag{1}$$

Where, P_{score}: Pressure consistency score, F_{score}: Flow rate stability score, E_{score}: Energy efficiency score, L_{score}: Leakage detection score, w_P, w_F, w_E, w_L: Weighted coefficients based on operational significance. The dynamics of control decision latency are represented as Eq. (2):

$$\frac{\partial C}{\partial t} = \lambda_c - \mu_c \tag{2}$$

Where, C: Control latency, λ_c: Data ingestion rate from sensor nodes, μ_c: Processing rate of the control model, Operational throughput is quantified as Eq. (3):

$$T_s = \frac{N_s}{\Delta t} \tag{3}$$

Where, N_s : Number of sensor and control events processed, Δt: Observation interval, Control overhead is further modeled as Eq. (4):

$$C_o = \int A(t)\, dt \tag{4}$$

Where $A(t)$ represents automated control actions over time. The system's resource utilization is expressed as Eq. (5):

$$U_s = \frac{R_{used}}{R_{total}} \tag{5}$$

Where, R_{used} : Utilized computational resources, R_{total} : Total available resources. The control efficiency of the model is calculated as Eq. (6):

$$\eta_c = \frac{C_{accurate}}{C_{total}} \times 100 \tag{6}$$

Where, $C_{accurate}$: Correct control decisions, C_{total} : Total control decisions, Control error is measured as Eq. (7):

$$E_{control} = C_{predicted} - C_{actual} \tag{7}$$

Optimized predictive control power is modeled as a function of system parameters, Eq. (8):

$$P_{control} = f(\lambda_c, \mu_c, U_s) \tag{8}$$

The water network dataset is represented as Eq. (9):

$$D_n(i,j,k) = \frac{O_{phase}(i) \cdot Metric(k)}{T(j)} \tag{9}$$

Where, i: Operational phase (sensing, control, maintenance), j: Time interval, k: Performance metric. The Network Efficiency Performance Index (NEPI) is defined as Eq. (10):

$$NEPI = \frac{\eta_c \cdot R_c}{C_{avg}} \tag{10}$$

Where: η_c : Control accuracy, R_c : Control reliability rate, C_{avg} : Average control latency.

4.1 Process Flow Diagram

Fig. 2 shows how IoT sensor data is integrated with cloud-based reinforcement learning analytics. controlling. Control actions are triggered when abnormal hydraulic conditions or leakage-related anomalies are detected through predictive analysis of real-time sensor data and reinforcement learning–based decision policies. The architecture supports: (1) Real-time decision-making, (2) an automated control change (3) archiving historical policies and updating policies.

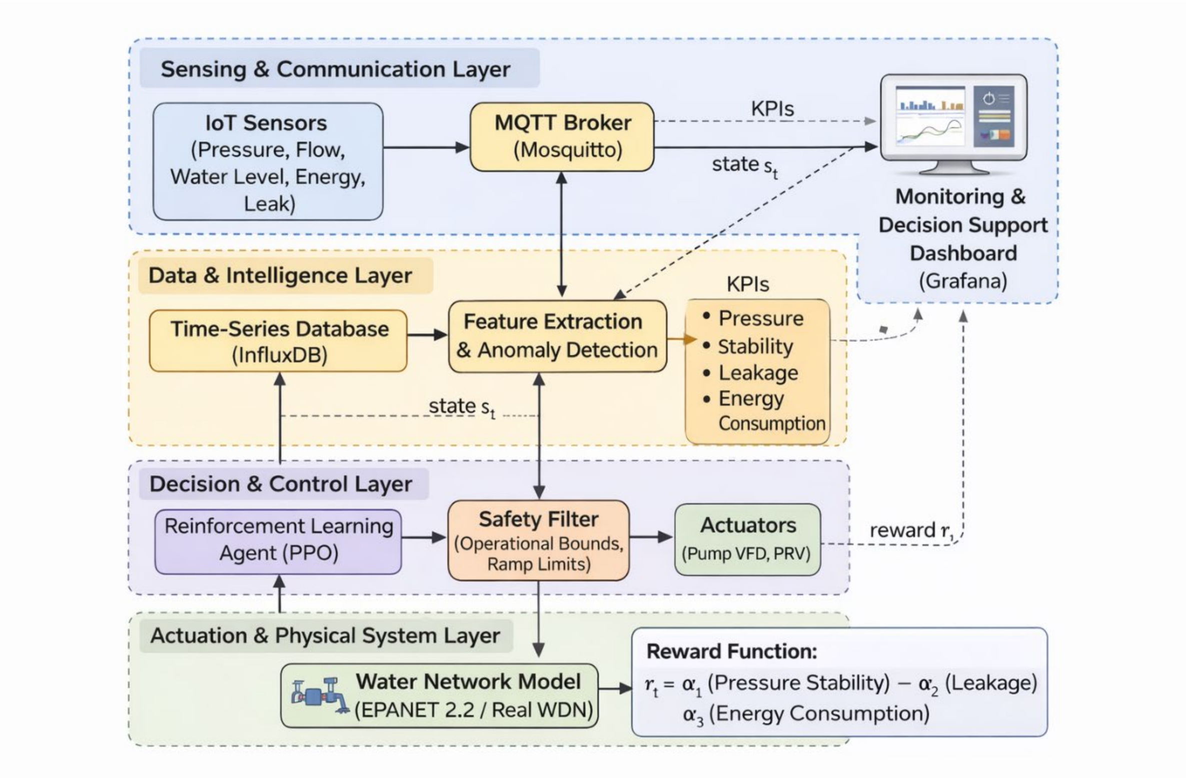

Fig. 2 *Water network control lifecycle with predictive optimization and adaptive control*

Figure 2 depicts the structure of the proposed IoT-enabled reinforcement learning system of smart water management, as structured into four layers connected with each other. At the sensing and communication layer, distributed IoT sensors constantly record the important hydraulic and operational parameters, including pressure, flow, water level, leakage, and energy consumption, and send the message through an MQTT broker. The data and intelligence layer stores streaming measurements in a time-series database and uses them to extract features and detect anomalies, producing answers in terms of system states and water management key performance indicators (KPIs).

The states are then sent to the decision and control layer, where a reinforcement learning agent using Proximal Policy Optimization (PPO) is trained to learn the controls, which are then provided to the safety filter to enforce operational bounds and smooth actuation. Validated control actions are used in the actuation and physical system layers to control actuators, such as variable-frequency-drive pumps and pressure-regulating valves, in a real or simulated water distribution network modeled in EPANET. A reward function, based on pressure stability, leakage, and energy efficiency, feeds back to the learning agent, and a monitoring and decision-support dashboard visualizes KPIs, anomalies, and control measures to facilitate continuous, adaptive, and data-driven water management.

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Random seeds and configuration files were fixed to achieve reproducible results (seed = 42; identical environment for all runs are the same). The pseudocode below is the adaptive control loop at the node level, which includes anomaly detection and predictive indices for real-time adjustments. Unlike Model A, which only depends on fixed threshold rules and lacks adaptive learning, Model B continually adapts its control policy based on operational feedback from the real-time sensor observations and reward-based learning.

```
Algorithm 1. Adaptive control
Initialize Pressure_Threshold, Flow_Limits, Resource_Capacity
For each Control_Node in Network:
  Measure: Pressure, Flow_Rate, Energy_Consumption, Leak_Indicator
  Calculate Real-Time NPI
  If (NPI < Performance_Threshold or Anomaly_Detected):
    Trigger Adaptive Control
    Adjust Pump_Speed or Valve_Position
    Log Event for Policy Update
  Compute Control Model Accuracy η_c
  Store Metrics in Central Database
End For
Evaluate NEPI for Overall Network Performance
```

To provide a fair and comprehensive benchmark, three control configurations were examined: Model A, a static threshold–based SCADA controller representing traditional rule-driven supervision; Model B, the proposed IoT–RL adaptive controller employing a Proximal Policy Optimization (PPO) policy with real-time feedback; and Model C, a baseline PID-based supervisory control commonly deployed in municipal networks. Model A relies on fixed limits for pressure and flow without contextual learning, while Model C introduces proportional–integral–derivative tuning to improve stability but lacks long-term adaptation. In contrast, Model B learns optimal actions through continuous interaction between the IoT sensor layer and the RL agent, enabling predictive leak mitigation and dynamic pump-valve coordination. Each model was evaluated under identical hydraulic and demand conditions within the EPANET-based simulation environment, using the same telemetry and actuator sets. A comparative assessment was conducted of latency, control accuracy, false-activation rate, throughput, and energy efficiency, providing a quantitative foundation for validating the benefits of the reinforcement-learning architecture over conventional threshold or PID controls.

4.2 Control Model Architectures for Comparative Analysis

The research uses three separate control models to test a performance spectrum:

- Model A (Static Threshold SCADA): This model involves fixed and pre-determined pressure and flow rate thresholds. Only based on these thresholds, control actions (e.g., pump on/off, valve adjustment) are activated, which are regarded as classic reactive SCADA systems.
- B. Model C (Hybrid PID-MPC): This architecture is an integration of the (robust in terms of errors) powerful models of the error-corrective Proportional-Integral-Derivative (PID) control and the prediction anticipation features of a Model Predictive Control (MPC) layer. The MPC forecasts, over a short horizon (e.g., 30-60 minutes), the state of the network using a simplified hydraulic model, and optimizes the setpoints for a set of underlying PID controllers. It is a model-based and advanced benchmark.
- C. Model B (Proposed Adaptive IoT-RL): A Proximal Policy Optimization (PPO) agent is used in this model and is trained by learning a control policy by interacting with the simulated environment. The agent is fed state information (pressures, flows, demands, expenses), is rewarded for efficiency, stability, and minimizing leakage, and produces control actions for pumps and valves. It does not require an explicit hydraulic model and optimizes long-term performance.

The PPO agent learned these state variables from the distributed IoT sensors based on pressure, flow rate, Tank level, energy consumption, and leakage. Adaptive operation of the pump speed and adjusting the position of the valve were added to the action space. A reward function was designed to balance energy usage, latency, false control activation, hydraulic stability, and leakage mitigation. The agent was able to continuously interact with the EPANET simulation environment for various demands and leakages to learn an optimal long-term control policy for the smart water distribution management.

5. Results and Discussion

The experiments were run on the C-Town benchmark (EPANET-based), which consists of 388 nodes, 429 pipes, 7 pumps, and 11 valves. The data that were analyzed are made available to the public [20]. Leaks (0.5–3.0 L/s) were injected into the demand patterns, which were varied ±20%. The simulation time was 24 h and a hydraulic step of 60 s. The controller ran with the PPO algorithm with $\alpha = 1$, $\beta = 0.5$, and $\gamma = 0.2$ with a decision interval of 5 min.

A comparative study among the static-threshold SCADA model (Model A), the hybrid PID-MPC controller (Model C), and the proposed adaptive IoT-RL controller (Model B) was made to evaluate the performance. The results show a clear performance difference, with Model B achieving excellent results in the areas of control accuracy, response time, and network efficiency, establishing a new benchmark for intelligent water distribution management.

Simulations were performed in a variety of demand and leakage conditions, following the PPO training process, through the EPANET 2.2 environment for multiple simulation episodes. In each episode, the agent monitored the state of the hydraulic network and chose adaptive control actions that would maximize network performance. Reward feedback on pressure stability, leakage reduction, energy efficiency, and response latency was used iteratively to update the policy. The training process lasted until the reward convergence and stable control behavior was realized over the various operating conditions.

5.1 Control Latency and Resource Cost

Model A had a minimum average time of 45 minutes, Hybrid PID-MPC (Model C) had a minimum average of 8 minutes, with the proposed Model B having a minimum of 3 minutes' latency. The control latency for each model is shown in Fig. 3.

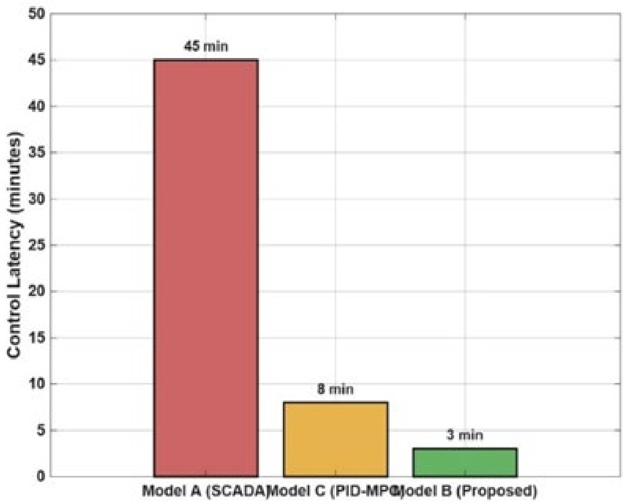


Fig. 3 *Control latency per operational cycle*

The predictive capability of Model C significantly improved response time compared to the reactive threshold-based Model A. However, the proposed Model B achieved the lowest latency because the PPO-based reinforcement learning agent continuously adapts its control policy according to real-time network conditions, enabling faster and more accurate leakage response decisions.

5.2 Control Model Accuracy

In Fig. 4, the control decision accuracy is compared.

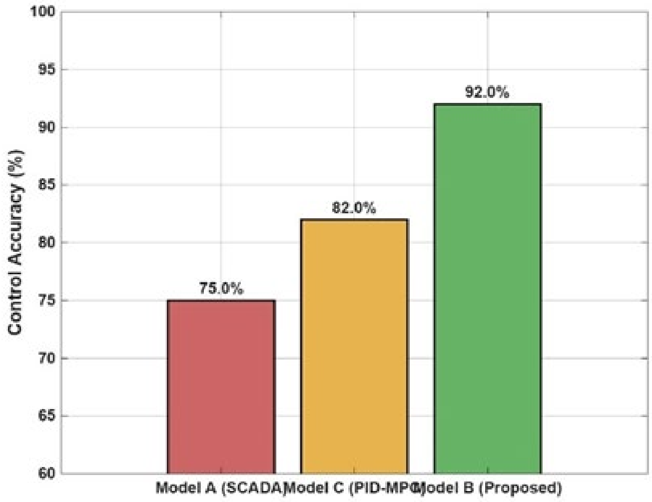


Fig. 4 *Control accuracy comparison*

Model A recorded an average control accuracy of 75.0%, while Model C achieved 82.0%. The proposed Model B produced the highest control accuracy of 92.0%, demonstrating the effectiveness of reinforcement learning in adapting to dynamic hydraulic conditions and improving decision precision. The improvement here simply shows that while the model-based prediction of Model C is significantly superior to the fixed threshold, the adaptive reinforcement learning of Model B is necessary for guaranteeing that optimization control of the dynamic network can be obtained.

5.3 Data Processing Throughput Stability

Fig. 5 illustrates that the average data throughput at Model A was 950 events/second.

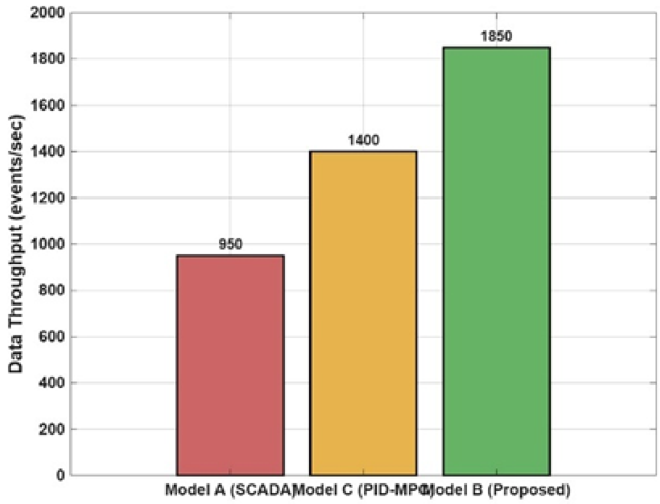


Fig. 5 *Operational data throughput per second*

The predictive control computations in Model C resulted in about 1,400 events per second. On the other hand, the proposed Model B had the best throughput of 1,850 events per second using its optimized reinforcement learning inference mechanism that showcased its superior efficiency at processing real-time operational data under varying network loads.

5.4 Control Reliability in Network Operations

The false rate of control activation is presented in Fig. 6.

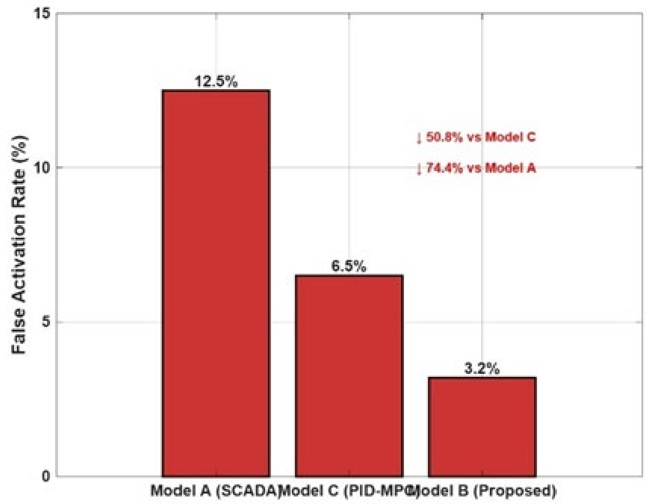
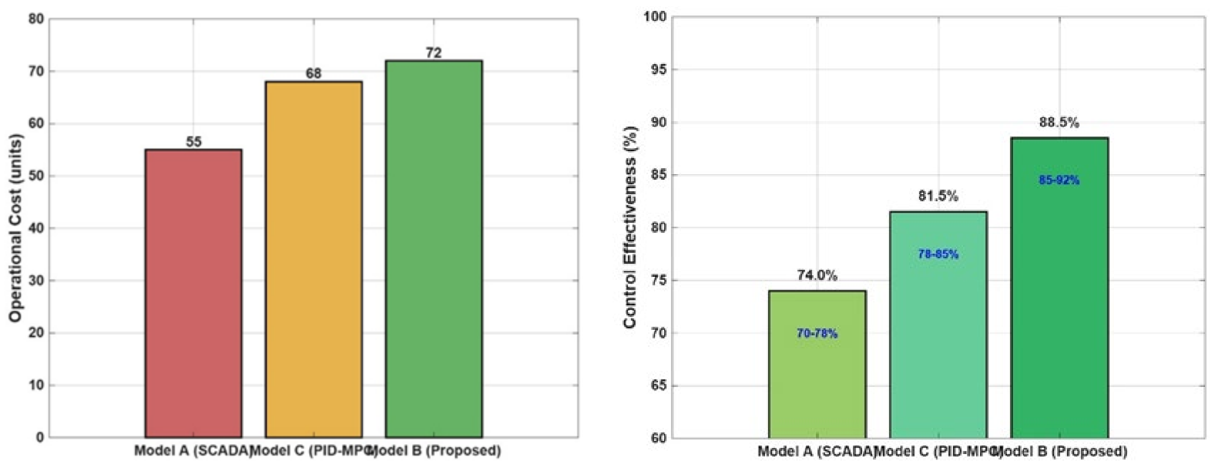


Fig. 6 *False control activation rate*

Model A produced a false control activation rate of 12.5%, while Model C reduced the rate to 6.5%. The proposed Model B achieved the lowest false activation rate of 3.2% due to the reward-guided learning strategy of the PPO agent, which minimizes unnecessary control actions and improves the stability and reliability of network operations.

5.5 System Cost and Performance Gains

Cost and control effectiveness in the system are described in Figs. 7 (a) and (b), respectively.



(a) Operational Cost Comparison **(b) Control Effectiveness per Operational Batch**

Fig. 7 *System cost and performance gains*

The operational costs of Model A, Model C and Model B are 55 units, 68 units and 72 units per cycle, respectively. The expensive adaptive models were needed to gain significantly improved control effectiveness, but they added significantly to the cost of operation. The early leak detection and control effectiveness with Model B was higher in the range of 85% to 92%, as compared to Model C (78%-85%) and Model A (70%-78%). The findings have shown that the operation cost of the proposed IoT-RL framework is worth the additional cost as it provides a significant improvement in network reliability, predictive control capability and sustainable water management performance.

5.6 Network Efficiency Performance Index

The comparison of the Network Efficiency Performance Index (NEPI) is made in Fig. 8.

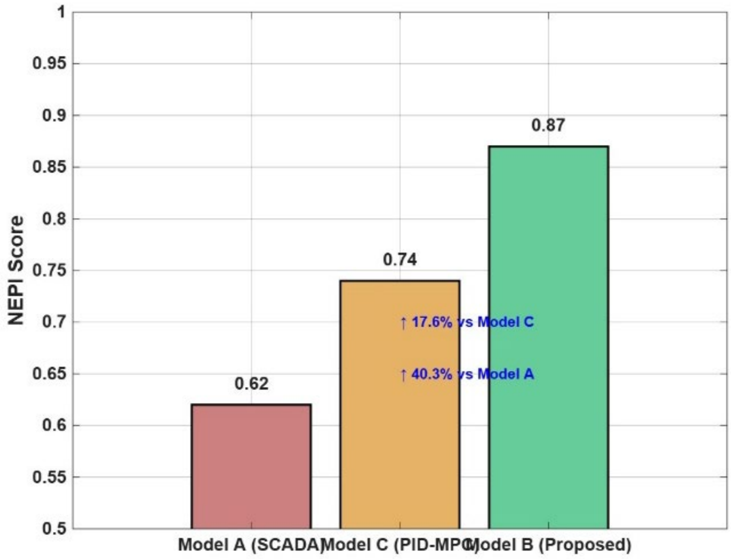


Fig. 8 *NEPI comparison*

This comprehensive performance indicator shows that the proposed adaptive IoT-RL architecture is effective for all major operational metrics: control accuracy, response latency, throughput stability and fault tolerance, with Model B being the best performance, that of Model C being 0.74 and Model A being 0.62.

5.7 Tabular Comparisons and Key Findings

All tables should be numbered with Arabic numerals. Every table should have a caption. Headings should be placed above tables. Only horizontal lines should be used within a table to distinguish the column headings from the body of the table and immediately above and below the table. Tables must be embedded into the text and not supplied separately. Below is an example that the authors may find useful.

Table 2 *Comparative control accuracy and latency metrics for Model A, Model C, and Model B*

Metric	Model A	Model C (Hybrid PID-MPC)	Model B (Proposed)	Improvement (B vs. A)	Improvement (B vs. C)
Avg. Control Accuracy (%)	75.0	82.0	92.0	↑ 22.7%	↑ 12.2%
Avg. Control Latency (minutes)	45	8	3	↓ 93.3%	↓ 62.5%
Control Model Efficiency (%)	72.3	80.5	88.5	↑ 22.4%	↑ 9.9%
Early Leak Detection & Control Rate (%)	70-78	78-85	85-92	—	—

Table 2 presents core control performance and shows that the proposed Model B is the most accurate and least latent, substantially outperforming both static and predictive benchmarks. System-level efficiency is summarized in Table 3, which shows that Model B achieves higher data throughput and operational reliability than Model A and a considerably lower false activation rate.

Table 3 *Comparative system performance and control metrics*

Metric	Model A	Model C (Hybrid PID-MPC)	Model B (Proposed)	Improvement (B vs. A)	Improvement (B vs. C)
Data Processing Throughput (events/sec)	950	1,400	1,850	↑ 94.7%	↑ 32.1%
False Control Activation Rate (%)	12.5	6.5	3.2	↓ 74.4%	↓ 50.8%
Resource Utilization (%)	52	65	75	↑ 44.2%	↑ 15.4%
Network Efficiency Performance Index (NEPI)	0.62	0.74	0.87	↑ 40.3%	↑ 17.6%

Overall, compared to Model A, the proposed Model B achieved 22.7% higher control accuracy and reduced control latency by 93.3%. Compared to Model C, Model B improved control accuracy by 12.2% and reduced latency by 62.5%. In addition, Model B increased data-processing throughput by 94.7% compared to Model A and by 32.1% compared to Model C, while reducing false control activations by 74.4% and 50.8%, respectively. The results in this work highlight the success of the proposed IoT-RL architecture for improving operational reliability, responsiveness of adaptive control, and the efficiency of real-time water distribution management.

The traditional SCADA constraints imposed on Model A are the use of fixed pores and the absence of its own predictors. The model C provides a significant improvement in model-based prediction and PID stability, but it is limited by the need to use a predetermined hydraulic model and cannot explore long optimization horizons. Model B, in turn, builds on model-free reinforcement learning to continuously improve its control policy in terms of long-term efficiency and network reliability. Model B offers better scalability for large-scale water distribution systems, as the performance gap between Figs. 4 and 6 decreases with increasing network load. Overall, Model B will be the foundation for the next-generation water management system, based on data and providing resource consumption and operational efficiency sustainability.

6. Conclusion

A proposed integrated model of IoT-reinforcement learning (RL) was hypothesized and proven to be effective for intelligent management of the Water Distribution Network (WDN) of the city. The system provided a high level of responsiveness and efficiency over the traditional supervisory methods through real-time sensing, adaptive control, and predictive analytics. The control policy of Proximal Policy Optimization (PPO) was applied in the EPANET 2.2 simulation environment, using the C-Town benchmark with diurnal demand variations. Three control systems were compared: the fixed-threshold SCADA model (Model A), the adaptive IoT-RL controller (Model B), and the supervisory control based on PID (Model C). The quantitative analysis demonstrated that Model B also decreased the control latency by about 93%, improved decision accuracy by 22%, and improved data-processing throughput by about 95% compared to Model A, and was additionally highly stable and energy-efficient compared to the PID baseline. In general, the findings support the notion that IoT-based reinforcement learning provides a scalable, data-driven foundation for sustainable, proactive water-infrastructure management. The current work will be expanded to multi-agent RL for the distributed pressure zone and to demand forecasting to more actively enhance resilience and provide predictive decision support in municipal water systems in the future.

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Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Ibraheem A Aidan, Mustafa M Aljumaily;* ***data collection:*** *Hussein Ali Mubarak AlMaqbali, Abdelrahman H. Hussein;* ***analysis and interpretation of results:*** *Hussein Ali Mubarak AlMaqbali, Abdelrahman H. Hussein;* ***draft manuscript preparation:*** *Ibraheem A Aidan, Mustafa M Aljumaily. All authors reviewed the results and approved the final version of the manuscript.*

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